Improved License Plate Recognition for Low-Resolution CCTV Forensics by Integrating Sparse Representation-Based Super-Resolution

Hyun-seok Min[1(✉)], Seung Ho Lee[1], Wesley De Neve[1,2], and Yong Man Ro[1]

[1] Image and Video Systems Lab, Korea Advanced Institute of Science and Technology (KAIST), Yuseong-gu, Daejeon, Republic of Korea
{hsmin, leesh09, wesley.deneve}@kaist.ac.kr, ymro@ee.kaist.ac.kr
[2] Multimedia Lab, Ghent University – iMinds, Gaston Crommenlaan 8 bus 201 9050 Ledeberg-Ghent, Belgium

Abstract. Automatic license plate recognition (LPR) is an important functionality for closed-circuit television (CCTV) forensics. However, uncontrolled capture conditions make it still difficult to achieve effective LPR in practice. In this paper, we propose a novel method for robust LPR in real-world imagery, leveraging sparse representation-based (SR-based) super-resolution. To that end, we make use of high-resolution license plate (LP) images that are used for both (1) the construction of a dictionary for SR-based super-resolution and (2) the training of LP character classifiers. Comparative experimental results indicate that the proposed SR-based super-resolution method allows for effective LPR in low-resolution imagery captured by long-distance CCTV cameras.

Keywords: Character recognition · CCTV video footage · License plate recognition · Sparse representation · Super-resolution

1 Introduction

Automatic license plate detection (LPD) and LPR are important functionalities for CCTV forensics, with both functionalities recently attracting considerable research attention [1, 2]. However, despite the significant progress that has been made during the past few years, it is still difficult to achieve effective LPR in real-world imagery, mainly due to the challenging nature of the capture conditions [3]. Indeed, long-distance CCTV cameras typically produce low-resolution LP images that contain a substantial amount of noise, and where the amount of noise is dependent on parameters like the capture distance, the illumination, and the type of CCTV camera used.

To improve the effectiveness of current LPR systems, image enhancement algorithms that take advantage of super-resolution methods have been proposed [4]. These methods aim at enhancing images by producing high-resolution images from one or

Y.Q. Shi et al. (Eds.): IWDW 2013, LNCS 8389, pp. 452–462, 2014.
DOI: 10.1007/978-3-662-43886-2_32,

more low-resolution images [5]. Many of these super-resolution methods focus on maximizing the signal-to-noise ratio (SNR) between the original high-resolution image and the reconstructed image [6]. However, in LPR, obtaining a higher SNR does not necessarily contribute to a higher recognition rate. Indeed, for recognition purposes, obtaining high-quality test images with characteristics that are similar to the characteristics of high-quality training images is typically more important than obtaining a higher SNR, given that classifiers take decisions based on the characteristics of training images. However, low-quality LP images used during testing can have characteristics that are very different from the characteristics of high-quality training images. In addition, while conventional super-resolution approaches target generic super-resolution, specific image priors (exemplars) can be incorporated that allow tailoring super-resolution to the LPR application domain.

In this paper, we propose a novel method for robust LPR in real-world imagery, leveraging sparse representation-based (SR-based) super-resolution. To that end, we make use of high-resolution LP images that are used for both (1) the construction of a dictionary for SR-based super-resolution and (2) the training of LP character classifiers. As shown by our comparative experimental results, this makes it possible to achieve effective LPR, even when making use of low-resolution images that have been captured by long-distance CCTV cameras.

The remainder of this paper is organized as follows. In Sect. 2, we discuss our overall approach towards the task of automatic LPR. In Sect. 3, we describe how to realize improved LPR by means of SR-based super-resolution. In Sect. 4, we report and analyze our experimental results. Finally, in Sect. 5, we present our conclusions and directions for future research.

2 Proposed Method

Figure 1 shows that the proposed LPR method mainly consists of three steps: (1) LPD; (2) SR-based super-resolution; and (3) LP character recognition. First, we extract LP images from input images that have been acquired by a real-world CCTV system deployed in Korea. Next, given that LP images are typically small and that LP images contain a substantial amount of noise, we enhance the resolution of the LP images so that they have characteristics that are similar to the characteristics of the high-quality training images used. To that end, we apply SR-based super-resolution, leveraging a dictionary that has been built by making use of high-resolution LP training images. We subsequently segment the super-resolution LP images into LP characters. Finally, we classify each LP character by means of trained classifiers.

3 Sparse Representation-Based Super-Resolution for LPR

Given that the distance between CCTV cameras and the LPs on cars of interest is usually large, resolution enhancement of LP images is desirable in CCTV application scenarios. In this context, we would like to make note that, unlike generic images, LP images have a structure that is more typical. Therefore, whereas most super-resolution approaches target generic image enhancement, specific image priors can be incorporated that allow tailoring super-resolution to the LPR application domain, such as information about the font, location, and color of LP characters. Furthermore, specific image priors can be shared if their target domains coincide. This is for instance the case for the proposed LPR method, where LP image priors are shared among the resolution enhancement and LP character recognition steps. Indeed, as shown by Fig. 1, we make use of high-resolution LP images that are used for both (1) the construction of a dictionary for SR-based super-resolution and (2) the training of LP character classifiers.

In order to enhance the resolution of a small LP image, we represent the LP image under consideration by means of a limited number of high-resolution LP images. To that end, we construct a dictionary that consists of a large number of LP image patches. Let $\mathbf{x}_i$ denote the feature vector of the i^{th} LP image patch extracted from the set of high-resolution training images. The dictionary D can then be defined as follows:

$$\mathbf{D} = [\mathbf{x}_1, \ldots, \mathbf{x}_i, \ldots, \mathbf{x}_K] \in \mathrm{R}^{d \times K} \tag{1}$$

where d is the dimensionality of the feature vectors and K the number of LP image patches in the dictionary.

Given a low-resolution LP image $\mathbf{Y}_l$ that has been obtained during the LPD step, we first extract low-resolution patches $\mathbf{y}_l$ from the LP image $\mathbf{Y}_l$. We then interpolate each local patch $\mathbf{y}_l$ by means of bicubic interpolation. Next, we compute the sparse representation of each interpolated local patch $\mathbf{y}_l^i$ by solving the following minimization problem:

$$\min_{\alpha} \left\| \mathbf{D}\alpha_l^i - \mathbf{y}_l^i \right\|_2^2 + \lambda \left\| \alpha_l^i \right\|_1 \tag{2}$$

where the parameter λ is used to balance the sparsity of the solution and the fidelity of the approximation to $\mathbf{y}_l^i$. In order to find the solution that is sparsest among all possible

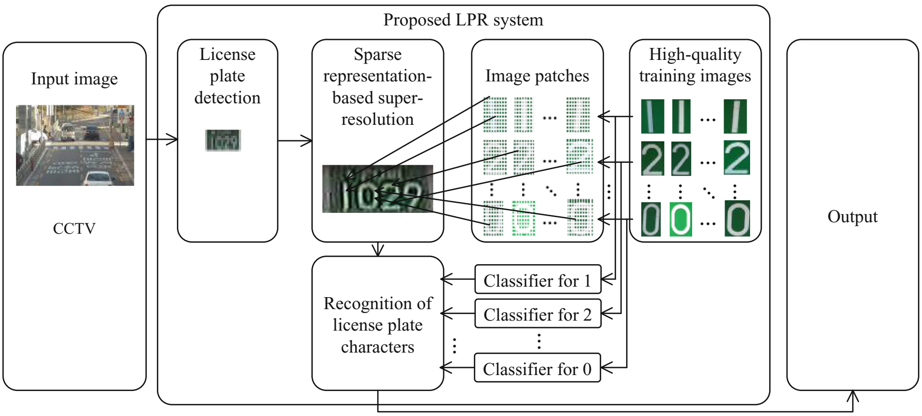


Fig. 1. Proposed LPR method.

solutions, we employ l_1-minimization [7]. Further, the super-resolution representation $\mathbf{D}\alpha_l^i$ of the local patch $\mathbf{y}_l^i$ is constrained to closely agree with the high-resolution LP image patches. Finally, we construct a high-resolution LP image $\mathbf{Y}_h$ by stitching together the super-resolution LP image patches. Algorithm 1 describes our SR-based super-resolution method by means of pseudo-code.

input: a low-resolution LP image ($\mathbf{Y}_l$), a dictionary that consists of high-resolutio
LP training images ($\mathbf{D}$)
output: a super-resolution LP image ($\mathbf{Y}_h$)

for each small image patch $\mathbf{y}_l$ (size: 5×5 pixels) extracted from LP image $\mathbf{Y}_l$
interpolate image patch $\mathbf{y}_l$
solve the following sparse representation problem:

$$\min_{\alpha} \left\| \mathbf{D}\alpha_l^i - \mathbf{y}_l^i \right\|_2^2 + \lambda \left\| \alpha_l^i \right\|_1$$

generate the high-resolution image patch $\mathbf{x} = \mathbf{D}\alpha_l^i$
put the patch into a high-resolution image $\mathbf{Y}_h$
end for

4 Experimental Setup

In this section, we first describe the test dataset used in our experiments. We then explain how we constructed a dictionary for SR-based super-resolution of LP images and how we trained LP character classifiers. Finally, we discuss how we measured the effectiveness of the proposed LPR method.

4.1 Test Dataset Used

To study the effectiveness of the proposed LPR method, we conducted experiments with 600 real-world input images. These input images, which were captured by long-distance CCTV cameras deployed in Korea, have a spatial resolution of 1280 × 720 pixels and contain one or more LP images. Figure 2 shows two example input images. We can observe that the two input images contain LP images that have a low spatial resolution.

We extracted 772 LP images from the 600 input images by making use of sliding concentric windows (SCW) [8]. The resolution of all LP images in the set of 600 input images varies from 50 × 13 to 120 × 30 pixels.

We divided the set of LP images into four groups, taking into account the spatial resolution of the LP images, thus making it possible to investigate the influence of the use of a low spatial resolution on the effectiveness of LPR. The four groups created are as follows:

Fig. 2. Example input images captured by long-distance CCTV cameras in Korea.

(1) Resolution Group 1: the width of the LP images is smaller than 40 pixels;
(2) Resolution Group 2: the width of the LP images is larger than 40 pixels and smaller than 55 pixels;
(3) Resolution Group 3: the width of the LP images is larger than 55 pixels and smaller than 70 pixels;
(4) Resolution Group 4: the width of the LP images is larger than 70 pixels.

Table 1 shows how the 772 LP images used are distributed over the four resolution groups defined. Further, Fig. 3 shows an example input image for each resolution group. We can observe that the distance between the CCTV camera and the vehicle of interest can vary substantially. In addition, we can observe that small LP images contain more blur when cars move or CCTV cameras shake.

We characterized image patches by means of color Gabor wavelet features [9, 10], applying Gabor filters to detect amplitude-invariant spatial frequencies [11]. Specifically, we characterized image patches by means of histograms of wavelet features, extracting a 1,000-D feature vector from each color channel of the HSV color space. This implies that we made use of feature vectors with a dimension of 3,000 (i.e., $d = 3{,}000$). Note that Gabor wavelet features have been widely adopted in the field of image recognition, given their robustness against illumination changes.

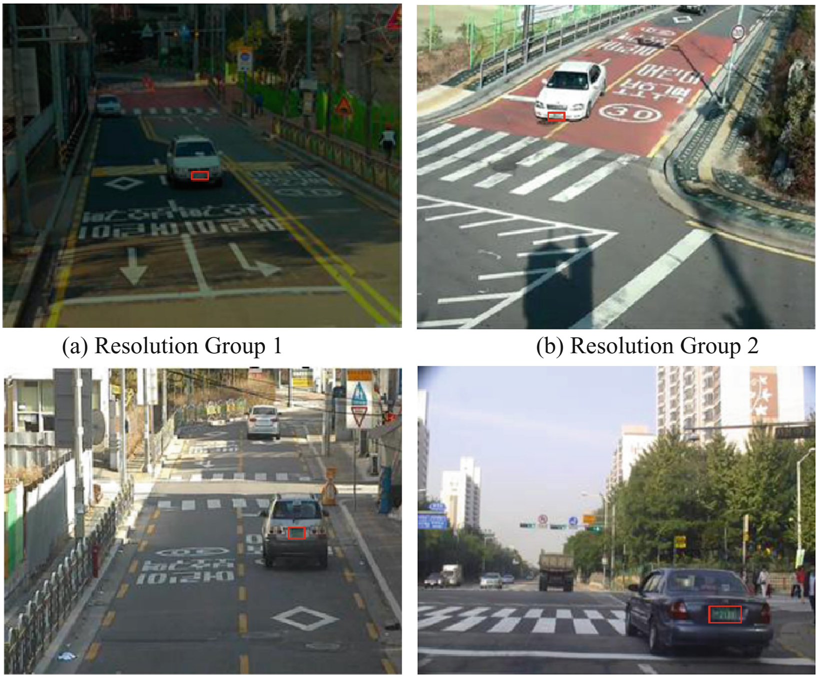
4.2 Dictionary Construction and Classifier Learning

For dictionary construction and classifier training purposes, we made use of 100 high-resolution LP images that have been downloaded via Google Image Search. Figure 4 shows a number of example LP images.

For dictionary construction purposes, we randomly extracted 10,000 image patches from the set of training images, with the image patches extracted having a size of 10×10 pixels. As such, in our experiments, we made use of a dictionary with a size

Table 1. Distribution of the 772 LP images in the 600 test input images over the four resolution groups defined.

Resolution group	1	2	3	4
Number of LP images	124 (16.1 %)	268 (34.7 %)	220 (28.5 %)	160 (20.7 %)



(a) Resolution Group 1 (b) Resolution Group 2

(c) Resolution Group 3 (d) Resolution Group 4

Fig. 3. Different types of LP images in the test dataset used. Red boxes are used to highlight an LP image (see the color version of the above images in the digital version of this paper).

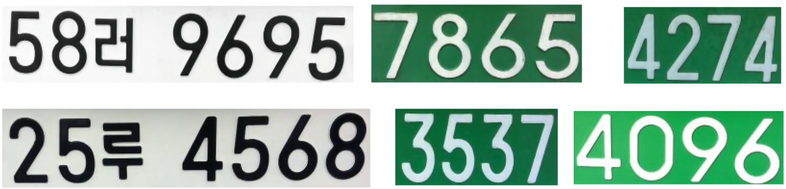


Fig. 4. Example high-resolution LP images.

of 10,000 (i.e., K = 10,000). In addition, in order to find the solution that is sparsest among all possible solutions, we performed l_1-minimization by making use of the regularized orthogonal least squares algorithm of [7]. Note that we set λ to a value of 0.5 (see Algorithm 1).

For LP character classification purposes, we adopted Support Vector Machines (SVMs), using a Radial Basis Function (RBF) as kernel. This type of SVMs is widely used [12]. Finally, we ran our experiments on a PC with an Intel 3.07 GHz Core i7 processor and 4 GB of system memory.

4.3 Metrics Used

We made use of the recognition rate to measure the effectiveness of the different LPR methods tested:

$$\text{Recognition rate} = \frac{N_{TP}}{N_{Total}}, \tag{3}$$

where N_{TP} denotes the number of LP images correctly recognized, and where N_{Total} denotes the total number of LP images used during testing (this is, N_{Total} is equal to 772). Further, in our experiments, we computed the effectiveness of LPR based on LP images that are true positives. This means that we assumed that the effectiveness of LPD detection is perfect. Finally, we measured the LPR effectiveness at the level of individual LP characters.

5 Experimental Results

This section reports our experimental results, studying how the effectiveness of LPR is influenced by (1) the use of different resolution enhancement methods, (2) the use of different dictionaries, and (3) the use of different low-level visual features.

5.1 Experiment I: Influence of Resolution Enhancement

In this section, we investigate how the use of different resolution enhancement methods influences the effectiveness of LPR. To that end, we enhanced the resolution of LP images by means of two methods: (1) the proposed SR-based super-resolution method and (2) bicubic interpolation.

Figure 5 allows comparing the influence of different methods for resolution enhancement on the effectiveness of LPR, for a varying spatial resolution of the LP

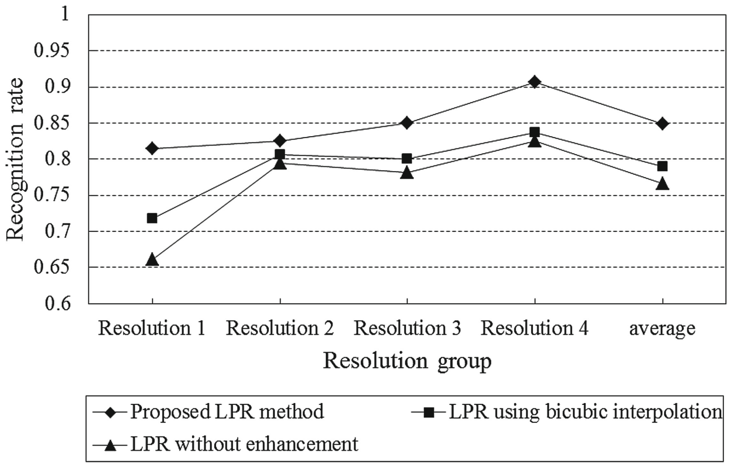


Fig. 5. Influence of different methods for resolution enhancement on the effectiveness of LPR, for a varying spatial resolution.

images. For the four resolution groups defined, we can observe that the effectiveness of the proposed LPR method is consistently higher than the effectiveness of LPR without resolution enhancement and the effectiveness of LPR using bicubic interpolation, and where the effectiveness of the former is also less dependent on the spatial resolution of the LP images. In addition, for the lowest spatial resolution (Resolution 1), we can observe that the effectiveness of the proposed LPR method is substantially higher than the effectiveness of LPR without resolution enhancement and the effectiveness of LPR using bicubic interpolation.

Figure 6 visualizes the output of the proposed super-resolution method and the method using bicubic interpolation. We can observe that the proposed SR-based super-resolution method generates results that are visually better than the results obtained by making use of bicubic interpolation.

5.2 Experiment II: Dictionary Influence

In this section, we study how the use of different dictionaries influences the effectiveness of LPR. To that end, we enhanced the resolution of the LP images by means of two types of dictionaries: (1) a dictionary consisting of high-resolution LP images, and where these high-resolution LP images are also used for training LP character classifiers (please see Sect. 4.2) and (2) a dictionary consisting of general images (e.g., images of flowers, buildings, leafs, and so on; please see Fig. 7).

Figure 8 allows comparing the influence of different dictionaries on the effectiveness of LPR, for a varying spatial resolution of the LP images. For the four resolution groups defined, we can observe that SR-based super-resolution by means of high-quality LP training images is more effective than SR-based super-resolution by means of general images. This can be attributed to the fact that the typical structure of LP images is different from the characteristics of the general images used.

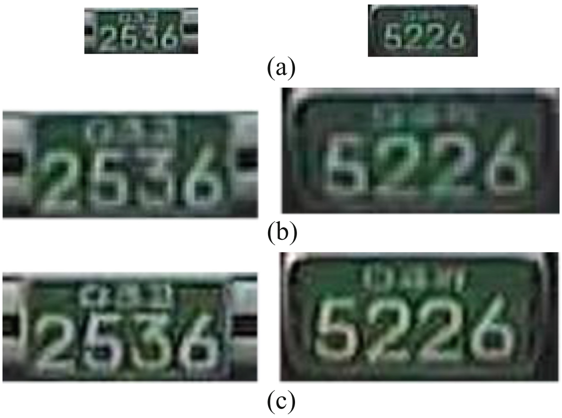


Fig. 6. Example LP images: (a) original low-resolution LP images, (b) LP images that are the output of bicubic interpolation, and (c) LP images that are the output of SR-based super-resolution. The resolution of the LP image to the left is 45 × 22 pixels (Resolution Group 2) and the resolution of the LP image to the right is 56 × 25 pixels (Resolution Group 3).

Fig. 7. Examples of general training images.

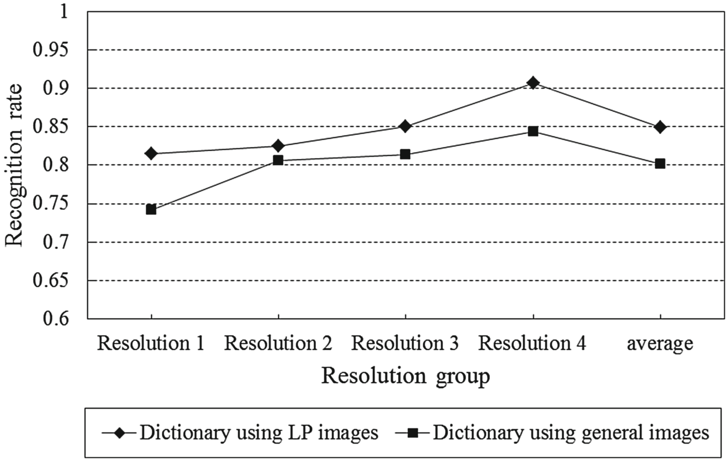


Fig. 8. Comparison of the influence of different dictionaries on the effectiveness of LPR, for a varying spatial resolution.

5.3 Experiment III: Influence of Low-Level Visual Features

In this section, we study how the use of different low-level visual features influences the effectiveness of the proposed LPR method. To that end, we characterized the LP image patches by means of four types of low-level visual features that are often used in the field of object classification: (1) raw pixel value features; (2) local binary pattern (LBP) features [13]; (3) Gabor wavelet features; and (4) color Gabor wavelet features [9, 10]. Note that we obtained the raw pixel value features of an LP image patch by simply concatenating the raw pixel values of that LP image patch.

Figure 9 allows comparing the influence of different low-level visual features on the effectiveness of LPR, for a varying spatial resolution of the LP images. We can observe that color Gabor wavelet features allow for the most effective LPR. For the lowest spatial resolution (Resolution 1), we can also observe that the two types of Gabor features allow for an LPR effectiveness that is substantially higher than the

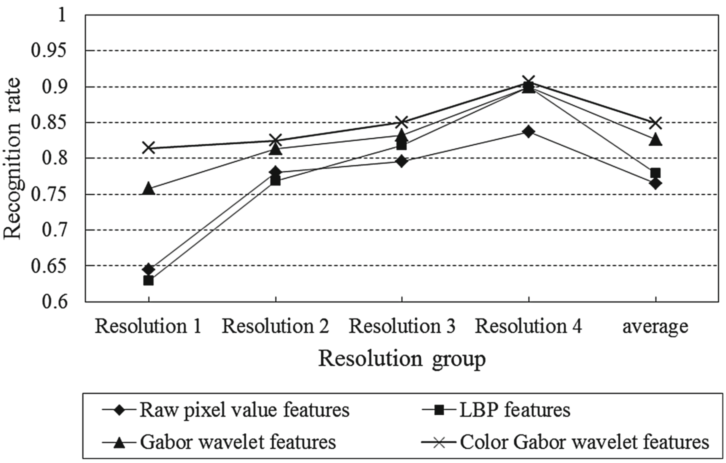


Fig. 9. Comparison of the influence of different low-level visual features on the effectiveness of the proposed LPR method, for a varying spatial resolution.

LPR effectiveness offered by raw pixel value features and LBP features. This can be attributed to the fact that Gabor features are known to be effective for describing the texture characteristics of low-resolution images.

6 Conclusions and Future Research

In this paper, we introduced a novel LPR method, leveraging SR-based super-resolution. In addition, the proposed LPR method makes use of the same set of high-quality LP images to facilitate SR-based super-resolution of LP test images and to recognize LP characters by means of SVM-based classifiers. To test the effectiveness of the proposed LPR method, we performed experiments with real-world CCTV input images, leading to the following observations:

- Our experimental results show that the effectiveness of the proposed method for LPR is on par with or better than the effectiveness of LPR using no resolution enhancement and the effectiveness of LPR using bicubic interpolation. This holds especially true for low-resolution LP images.
- Our experimental results demonstrate that SR-based super-resolution allows improving the effectiveness of LPR in real-world imagery. This holds especially true when dictionary construction and classifier training make use of the same set of high-quality LP training images.
- Our experimental results demonstrate that color Gabor wavelet features can be effectively used for LPR in real-world imagery. This holds especially true for low-resolution LP images.

In future research, we plan to conduct experiments with more advanced interpolation and super-resolution methods. In addition, we plan to analyze the computational complexity of the proposed approach.

Acknowledgment. This work was supported by a grant from the National Research Foundation (NRF) of Korea (grant number: NRF-2012K2A1A2033054).

References

1. Wen, Y., Lu, Y., Yan, J., Zhou, Z., von Deneen, K.M., Shi, P.: An algorithm for license plate recognition applied to intelligent transportation system. IEEE Trans. Intell. Transp. Syst. **12**(3), 830–845 (2011)
2. Du, S., Ibrahim, M., Shehata, M., Badawy, W.: Automatic license plate recognition (ALPR) a state of the art review. IEEE Trans. Circ. Syst. Video Technol. (99), 42–53 (2012)
3. Anagnostopuolos, C.-N.E., Anagnostopoulos, I.E., Psoroulas, I.D., Loumos, V., Kayafas, E.: License plate recognition from still images and video sequences: a survey. IEEE Trans. Intell. Transp. Syst. **9**(3), 377–391 (2009)
4. Li, Z., Han, G., Xiao, S., Chen, X.: MAP-based single-frame super-resolution image reconstruction for license plate recognition. In: Proceedings of the International Conference on Pattern Analysis and Intelligent Robotics (ICPAIR) (2011)
5. Park, S.C., Park, M.K., Kang, M.G.: Super-resolution image reconstruction: a technical overview. IEEE Signal Process. Mag. **20**(3), 21–36 (2003)
6. Farsiu, S., Robinson, M.D., Elad, M., Milanfar, P.: Fast and robust multiframe super resolution. IEEE Trans. Image Process. **13**(10), 1327–1344 (2004)
7. Wright, J., Yang, A., Ganesh, A., Sastry, S., Ma, Y.: Robust face recognition via sparse representation. IEEE Trans. Pattern Anal. Mach. Intell. **31**(2), 210–227 (2009)
8. Anagnostopoulos, C., Anagnostopoulos, I., Kayafas, E., Loumos, V.: A license plate recognition system for intelligent transportation system applications. IEEE Trans. Intell. Transp. Syst. **7**(3), 377–392 (2006)
9. Choi, J.Y., Ro, Y.M., Plataniotis, K.N.: Color local texture features for color face recognition. IEEE Trans. Image Process. **21**(3), 1366–1380 (2012)
10. Choi, J.Y., Ro, Y.M., Plataniotis, K.N.: Boosting color feature selection for color face recognition. IEEE Trans. Image Process. **20**(5), 1–10 (2011)
11. Xie, S., Shan, S., Chen, X., Chen, J.: Fusing local patterns of Gabor magnitude and phase for face recognition. IEEE Trans. Image Process. **19**(5), 1349–1361 (2010)
12. Müller, K.-R., Mika, S., Rätsch, G., Tsuda, K., Schölkopf, B.: An introduction to Kernel-based learning algorithms. IEEE Trans. Neural Netw. **12**(2), 181–201 (2001)
13. Ahonen, T., Hadid, A., Pietikainen, M.: Face description with local binary pattern: application to face recognition. IEEE Trans. Pattern Anal. Mach. Intell. **28**(12), 2037–2041 (2006)